



## VIDEO BASED VEHICLE DETECTION USING MORPHOLOGICAL OPERATION AND HOG FEATURE EXTRACTION

A. Shakin Banu and P. Vasuki

ECE, K.L.N. College of Information Technology, Sivagangai, India

E-Mail: [banu\\_shakin@rediffmail.com](mailto:banu_shakin@rediffmail.com)

### ABSTRACT

Vehicle detection plays an effective and significant role in the area of traffic surveillance system, where efficient traffic management and safety is the main concern. In this paper, the video based vehicle detection method using morphological operations and Histogram of Gradient (HOG) feature is proposed. The ROI region is selected and the pixels inside the selected ROI regions alone were detected. Sobel operator is used for the identification of the edge pixels. The gradient is obtained by finding the common pixels in the detected edge and the ROI regions. Finally, the object detection process is employed using Morphological process and Histogram Of gradient Process. Thus, a success rate of around 83% of accuracy is achieved in vehicle detection using proposed method.

**Keywords:** vehicle detection, Histogram of Gradients (HOG), traffic surveillance, Region of Interest (ROI), gradient.

### 1. INTRODUCTION

The number of cars on the roads increases with every passing year. Unfortunately, the number of accidents tends to be proportional with this increase. Nowadays, many vehicles are augmented with conventional driver assistance systems (DAS) such as: sensorial-informative (rear-view alarm, radar, lane departure warning system, etc.), actuation-corrective (anti braking system – ABS, emergency braking assistance – EBA, electronic stability control –ESC), and systemic (parking aids, distance control assist system, etc.). All the above systems are already implemented and designed to improve the traffic safety and to hopefully reduce the number of accidents, mostly caused by human driver errors. Consequently, forward collision warning system (FCWS) have become increasingly important for drivers. When vehicles are involved in a scene, road marks, signage, street lamps, or traffic signals could result in inaccurate vehicle detections. Moreover, the type of vehicles, and their rear profiles differ. However due to the large amount of vehicles, it is unreliable and difficult for manual operation. And traditional methods based computer vision and machine learning may also fail in some complicated scenarios.

This work presents a vision-based system for vehicle detection in videos acquired from a moving vehicles, it finds wide applications such as traffic surveillance, traffic management, transportation planning and intelligent traffic guidance systems etc. The area underneath a vehicle is distinctly darker than any other area on the road, shadow features [1] [2] [3] are typically use as a point of reference for detecting forward vehicles. However, the intensity of shadows depends on the illumination and weather conditions. Nowadays, many vehicles are augmented with conventional driver assistance systems detecting forward vehicles. Nowadays, many vehicles are augmented with conventional driver assistance systems detecting forward vehicles. However, the intensity of shadows depends on the illumination and weather conditions. In [4] edges were extracted separately using Sobel filter. However scenes contain numerous

features, such as road lines or road marks on the road. Determining how to identify vehicle edges has become a crucial concern. Wang [5] proposed a vehicle detection algorithm by using taillight as a point of reference, this algorithm is suitable for night time only. In [6] the methods mostly use the edges in the vehicle to identify the moving objects in the screen through frame differencing methods.

To more efficiently obtain traffic information from moving vehicles, techniques based on frame differencing [7] - [12] have been applied to differentiate moving vehicles from motionless background scenes based on change detection or other statistical models. Other studies [7] [8] uses spatial temporal difference features to segment moving vehicles, while the methods in [9]-[12] utilize techniques based on background subtraction to extract moving vehicles. These methods can be efficiently applied to daytime traffic scenes with stationary and unchanged lighting conditions. However, spatial-temporal difference features are no longer reliable when vehicles stop or move slowly in congested traffic areas, and vehicles may be falsely detected as background regions and missed. Moreover, in poorly illuminated or night time conditions, background scenes are substantially affected by the lighting effect of moving vehicles, making reliable hypotheses of background models which are effective for vehicle detection during daytime invalid. Thus, most of the frame-differencing techniques may be unreliable for handling nighttime and congested traffic environments. The proposed method efficiently detect the vehicles on the road regions, by histogram of gradients (HOG).

### 2. METHODOLOGY

In proposed method, the vehicle detection is done by employing morphological operations and feature extraction by HOG. In proposed work input video is taken and converted in to frames which includes seven modules, i. Preprocessing, ii. ROI Selection, iii. Edge detection, iv. Gradient Calculation, v. Morphological operations vi.



Feature extraction, vii. Detected Objects. The block diagram of proposed method is represented in Figure-1.

### A. Preprocessing

The preprocessing process includes basic operations such as frame conversion, resizing and filtering using some filters. Here median filter also called as order statistics filter is chosen for the preprocessing operation, it is widely used because under certain conditions, it preserves edges while removing noise. The filter selects a window size, the pixels within the specified window size is taken. The noisy pixel is identified and it is replaced by calculating the median of the neighboring pixels. Thus the filtering process makes the image (frame) pixels to look smoothened.

### B. Region of Interest (ROI) selection

To reduce the memory consumption and computation time, regions of interest (ROI) are defined based on the scene and camera type. The road regions in the images were selected as ROI.

- The ROI is selected manually in the first frame. The image pixels within the particular regions in all over the frames were calculated.
- The position of the needed locations were identified and the pixels within the regions were selected.
- The data set consist of 120 frames, the process is repeated all over the frames.

### C. Sobel edge Detection

Sobel operator is applied to the frames and the edge regions were detected. sobel operator is a discrete differentiation operator, computing an approximation of the gradient of the image intensity function. At each pixel in the image, the result of the sobel operator is either the corresponding gradient vector or the norm of this vector. The sobel operator is based on convolving the image (frames) with in a small, separable and integer valued filter in horizontal and vertical direction. Therefore it is relatively inexpensive in terms of computations. The pixels that are similar in both ROI and the edge detected pixels were identified.

### D. Gradient Calculation

Gradient is the combination of edge pixel, where each pixel is represented by its orientation and direction. Each pixel of a gradient image measures the change in intensity of that same point in the original image in a given direction. To get full range of direction, gradient images in x and y directions are computed.

- The gradient calculation refers to the identification of the pixel coefficients in the images.

- Here the image pixels that are commonly identified in both the ROI and the edge detection process is taken.

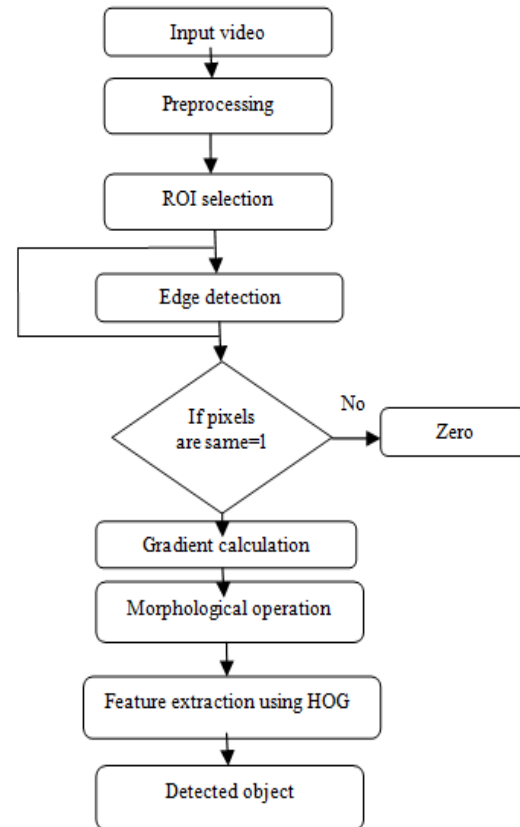


Figure-1. Flow diagram of proposed vehicle detection.

- The image pixels were compared and the pixels in the matching locations were identified.
- The pixels were then arranged in a matrix so that the image pixels that are not segmented is removed.
- The obtained image pixels consists of the reduced image pixels compared to the detected ROI and Edge detection.

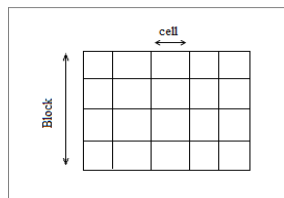
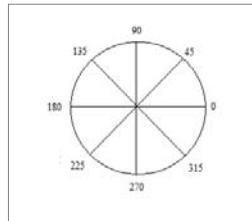
### E. Morphological Operations

The object detection process is employed using morphological operations and histogram of gradients (HOG). The objects in the video is detected by employing morphological operations using dilation. The object detection process is employed by filtering the results obtained from gradient in order to remove the excess objects segmented or detected, so that it further reduces the number of pixels in the frames. The detected objects were refined further to obtain the object alone. (eg. road marks, signage and overpass are almost eliminated).



### F. Histogram of Gradients (HOG)

Finally HOG is applied to the resulting object to detect the vehicle. Histograms of Oriented Gradients or HOG has been used to refer to a number of unique but related features. HOG is a standard image feature among others in object detection. Implementation done by dividing the image in to small connected regions called cells, for each cell it compiles a histogram of gradient directions. Cells themselves can be either rectangular or radial in shape. Combination of histogram represents the descriptors.



HOG descriptor has advantage over other descriptors, because it operates on localized cells. Gradient histogram measures the orientation and strength of image gradients within an image region. Gradient based feature descriptors are developed for object detection.

1. Global descriptor for complete object.
2. Very high dimensional (typically ~4000 dimensions).
- Partition image in to blocks at multiple scales and compute histogram of gradient orientations in each (cell) block.
  1. Each cell contains a local histogram over orientation bins.
  3. At each pixel, image gradient vector is calculated.

At last, all the vehicles are detected in the videos by the use of bounding box.

### 3. EXPERIMENTS AND RESULTS

In this experiment, the dataset is collected from google's earth, Figure-2. Shows the input video, it consist of 120 frames. In frame conversion it first checks the given dataset is in video (by height, width) is shown by Figure-3. Preprocessing is done by median filter, it preserves the edges while removing the noise, is shown by Figure-4.



Figure-2. Input video.

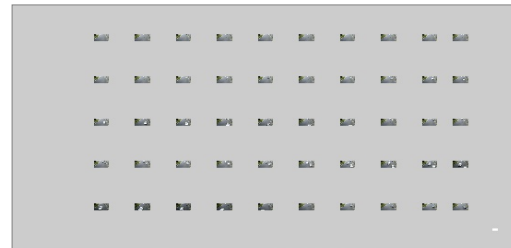


Figure-3. Number of frames in video.

Our aim is to detect the vehicles on road side, so road regions are selected as ROI, here roipoly function is used because road may be of any shape. ROI is chosen manually, the position of the needed locations were identified and the pixels within the regions were selected and the process is repeated all over the frames in the video. The main advantage of ROI was it reduces the memory consumption and computation time, is shown by Figure-5a and Figure-5b.



Figure-4. Preprocessing by median filter.

Figure-6. Shows that edges are detected using sobel filter. At each point in the image, the result of the Sobel operator is either the corresponding gradient vector or the norm of this vector. In Figure-7. It show that, the gradient is obtained by finding the common pixels in the detected edge and the ROI regions. The image pixels were compared and the matching locations in the pixels were identified. The pixels were then arranged in a matrix so that the image pixels that are not segmented is removed. The obtained image pixels consists of the reduced image pixels compared to the detected ROI and Edges.

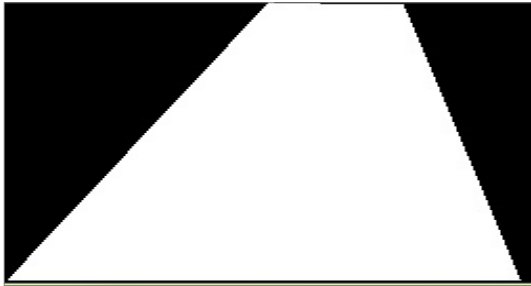


Figure-5(a). ROI mask.



Figure-5(b). ROI selected in road regions.



Figure-6. Edge detection using sobel filter.



Figure-7. Gradient image.

Figure-8.a and Figure-8.b shows that objects are detected by using morphological operation and HOG. The objects in the video is detected by employing morphological operations using dilation is done by filtering the results obtained from gradient in order to remove the excess objects segmented or detected. Morphological operations using dilation of disk shaped

structuring element were employed for the filtering process, it further reduces the number of pixels.



Figure-8(a). Morphological operations using dilation.

HOG is mainly an object orientation, it is used to measure the intensity difference in the particular region of an object. For improved accuracy, the local histograms can be contrast normalized by calculating a measure of the intensity across a larger region of the image, called a block, and then using this value to normalize all cells within the block. This normalization results in better invariance to changes in illumination or shadowing. In HOG, x and y coordinates are selected in the pixel and gradient is calculated, finally the magnitude and direction is obtained, for one frame it consist of 81 values. The value of  $m \times n$  for HOG is  $120 \times 81$ . It shows better performance in characterizing object shape and appearance. Figure-8.b shows that the vehicles are detected in the video.



Figure-8(b). Detected vehicles in video using HOG

#### 4. PERFORMANCE MEASURES

The accuracy and error rate calculated for all (120) frames, by using the formula. For example, Figure-9 shows that accuracy and error rate calculated for first 15 frames.

$$ACC = \frac{(TP + TN)}{(FP + TN) + (TP + FN)}$$



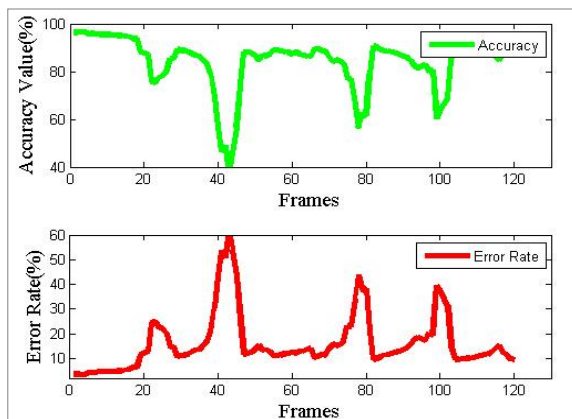
Where, TP and TN represent the total number of correctly detected true positive and true negative patterns. The FP and FN represent the total number of false positive and false negative patterns.

	Accuracy(%)	Errorrate(%)
1	96.4319	3.5681
2	96.4441	3.5559
3	96.5753	3.4247
4	96.6026	3.3972
5	95.7666	4.2334
6	95.8353	4.1647
7	95.7681	4.2319
8	95.4202	4.5798
9	95.3851	4.6149
10	95.3378	4.6622
11	95.3989	4.6011
12	95.2219	4.7781
13	95.1074	4.8926
14	95.0143	4.9857
15	94.7549	5.2451

**Figure-9.** Accuracy and Error rate for first 15 frames.

- True positive (TP) = correctly identified
- False positive (FP) = incorrectly identified
- True negative (TN) = correctly rejected
- False negative (FN) = incorrectly rejected

Figure-10, and Table-1 shows that performance graph and performance measures for both accuracy and error rate. Thus the overall accuracy and error rate is calculated by taking mean for all 120 frames.



**Figure-10.** Performance graph for HOG.

**Table-1.** Performance measures for hog.

Performance Measures for Hog	
Accuracy rate	error rate
83.8564%	16.1436%

## 5. CONCLUSION

Detecting vehicles on road is challenging task. In this paper, vehicle detection method based on morphological operation and HOG feature extraction was proposed. The mean accuracy rate of the proposed method was 83.86% and the error rate was 16.14%. The results demonstrate that the algorithm (HOG) is an efficient

feature extraction for detecting the vehicles. The results obtained can be very useful for traffic analysis, management and surveillance. The future work can be enhanced by identification of vehicle size and the identified size is compared with a threshold to find whether the object is car or truck.

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